Comparison between Wavelet and Radial Basis Function Neural Networks for GPS Prediction

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ABSTRACT
Neural networks are complex non-linear models; this characteristic enables them to be used in nonlinear system modeling and prediction applications. The estimation and prediction are important roles in the communication system. The proposed approach based on the Wavelet Neural Networks (WNNs) uses morlet as an activation functions in the hidden layer of the wavelet neural network, while the Radial Basis Function Neural Networks (RBFNNs) uses basis function that can be calculated as a Gaussian function. In this paper, a comparison between the performance of Wavelet Neural Networks and Radial Basis Function for GPS prediction is presented. The comparison results (using MATLAB programming) present that the Wavelet Neural Networks method has a great approximation ability, suitability and more stable in Global Positioning System (GPS) prediction than the Radial Basis Function Neural Networks, were highly effective predictions for accurate positioning and RMS errors were 0.05 meter after using of Wavelet Neural Networks prediction.

Keywords: Wavelet Neural Networks (WNNs), Global Positioning System (GPS) predictor, Radial Basis Function Neural Networks (RBFNNs).

مقارنة بين طريقتي (Wavelet) و(Radial Basis Function) للشبكات العصبية للتنبؤ بمنظومة الموقع العالمي (GPS)

الخلاصة:
تعتبر ألشبكات العصبية موديل غير خطي معقد, مما يجعل هذه الخصائص للشبكات العصبية القابلية على الاستخدام في الأنظمة غير ألخطية وفي تطبيقات التنبؤ. التخمين والتنبؤ من المهام المهمة في أنظمة الاتصالات، الدالة المستخدمة بطريقة (WNNs) هي دالة (morlet) باعتبارها وظائف التنشيط في الطبقة الخفية للشبكات

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العصبية, بينما المستخدمة بطريقة (RBFNNs) هي دالة (basis function) التي يمكن أن تحسب بوصفها (Gaussian function). تم في هذا البحث مقارنة أداءWavelet Neural Networks (WNNs) مع Radial Basis Function Neural Networks (RBFNNs) لتنبؤ قراءات منظومة أل GPS. بينت نتائج المقارنة (باستخدام لغة البرمجة MATLAB) أن طريقة Wavelet Neural Networks لديها القدرة الكبيرة للتقرب والملائمة وأكثر أستقرارية في تنبؤ قراءات منظومة الموقع العالمي (GPS) من طريقة Radial Basis Function, وكانت التوقعات فعالة للغاية لتحديد المواقع بدقة وان Min RMS للخطاء يصل إلى اقل من 0.05 متر بعد استخدام طريقة Wavelet Neural Network.

INTRODUCTION

Precise Global Positioning System (GPS) kinematic positioning in the real time mode is now increasingly used for many surveying and navigation applications on land, at sea and in the air. The GPS, error can be defined as any deviation in position from the true position. Some errors are natural phenomena while others are intentional. These errors can combine and become large errors. The most important errors include; satellite/receiver clocks, satellite orbits, prediction of atmospheric delays, multipath, Selective Availability (SA) and GPS receivers' internal circuitry [1]. Wavelet Neural Networks (WNNs) represent a fruitful synthesis of ideas from NNs and wavelet analysis. The utility of wavelet in nonlinear system modeling and approximation was demonstrated in [2]. Radial Basis Function (RBF) network is a special type of neural network that uses a radial basis function as its activation function [3]. RBF networks are very popular for function approximation, curve fitting, time series prediction, control, and classification problems. The radial basis function network is different from other neural networks, possessing several distinctive features, because of their universal approximation, more compact topology and faster learning speed, RBF networks have attracted considerable attention and they have been widely applied in many science and engineering fields [4, 5]. This paper presents a short-term prediction of GPS based on the Wavelet Neural Networks (WNNs) and (RBF) Network's. Each Wavelet and RBF Neural Networks predicts the GPS future values based on the past data with different time Sample.

Wavelet Neural Networks (WNNs)

A wavelet is a waveform of effectively limited duration that has an average value of zero. Wavelet analysis is the breaking up of a signal into shifted versions of the original wavelet. Wavelets are mathematical functions that cut up the data into different frequency components, and then study each component with resolution matched to scale [6, 7, 8]. WNNs combine the theory of wavelets and neural networks into one, it's generally consists of a feed-forward neural network, with one hidden layer, whose activation functions are drawn from an orthogonal wavelet family. There are two main approaches to creating wavelet neural networks:

- In the first, the wavelet and the neural network processing are performed separately. The input signal is first decomposed using some wavelet basis by the neurons in the hidden layer. The wavelet coefficients are then output to one or more summers whose input weights are modified in accordance with some learning algorithm.
- The second type combines the two theories. In this case translation and dilation of the wavelets along with the summer weights are modified in accordance with some learning algorithm [9].

Fig.(1), represent a kind of three layers WNN structure with both "wavlon nonlinearity" and "sigmoid neuron nonlinearity" [10].

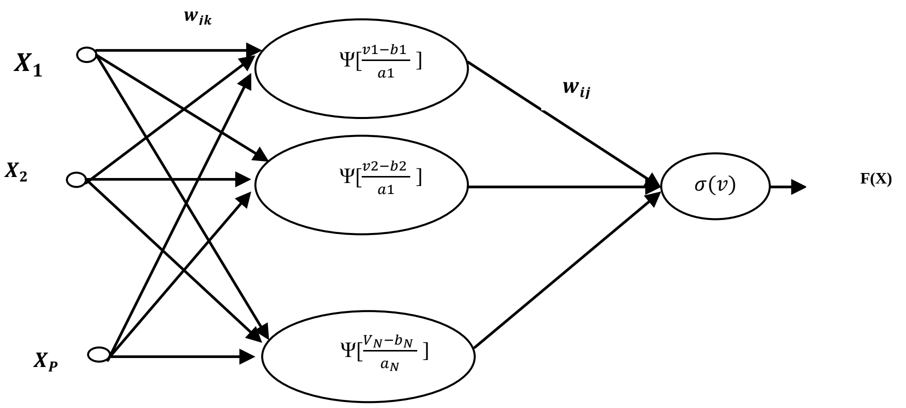


Figure (1): Three Layer of WNN.

This network consists of three layers; an input layer, a hidden layer, and an output layer. The input layer has *M* nodes. The output layer has only one neuron whose output is the signal represented by the weighted sum of several wavelets. The hidden layer is composed of a finite number of wavelets representing the signal.

Forward Calculations for WNN

The network consisting of total of *N* neurons in hidden layer, with *M* external input connections (as shown in Fig.1). Let $X(n)$ denotes the *M -by* -1 external input vector applied to the network, $y(n)$ denotes the output of the network, $w_{jk}(n)$ presents the weight between the hidden unit *j* and input unit *k* , $w_{ij}(n)$ denotes the connection weight between the output unit *i* and hidden unit *j* , $a_j(n)$ and $b_j(n)$ represents the dilation and translation coefficients in the hidden layer at discrete time n, respectively.
The net internal activity of neuron *j* at time *n*, is given by [10, 11]:

$$v_j(n) = \sum_{k=0}^{k=m} w_{jk}(n) * x_k(n) \quad \dots (1)$$

Where,
$v_j(n)$ is the sum of inputs to the *j th* hidden neuron, $x_k(n)$ is the *k th* input at time *n*. The output of the *j th* neuron is computed by passing $v_j(n)$ through the wavelets $\psi_{a,bj}(\cdot)$,

where:

$$\Psi_{a,b}[v_j(n)] = \Psi[(v_j(n) - b_j(n)) / (a_j(n))] \quad \dots (2)$$

The sum of inputs to the output neuron is obtained by[12]:

$$v(n) = \sum_{j=0}^{j=N} w_{ij}(n) * \Psi_{a,b}[v_j(n)] \quad \dots (3)$$

The output of the network is computed by passing $v(n)$ through the nonlinear function σ , obtaining:

$$y(n) = \sigma[v(n)] \quad \dots.. (4)$$

Learning Algorithm for WNN

The instantaneous sum of squared error at time *n* is [13]:

$$E(n) = \frac{1}{2} e^2(n) = \frac{1}{2}[y(n) - d(n)]^2 \quad \dots.. (5)$$

Where

$d(n)$ denote the desired response of output at time n. To minimize the above cost function, then the method of steepest descent is used. The weight between the hidden unit j and input unit k can be adjusted according to [14] :

$$\Delta w_{jk}(n+1) = -\eta * \frac{\partial E(n)}{\partial w_{jk}(n)} + \mu * \Delta w_{jk}(n)$$

$$= \eta * e(n) * \sigma\,[v(n)] \,\grave{*}\, w_{ij}\,(n) * \Psi_{a,b}\big[v_j(\acute{n})\big] \;*\; \frac{x_k\,(n)}{a_{j\,(n)}} + \mu * \Delta w_{jk}(n) \qquad \dots (6)$$

Where

η, is a learning rate. The connection weight between the output unit i and hidden unit j is updated as follow:

$$\Delta w_{ij}(n+1) = -\eta * \frac{\partial E(n)}{\partial w_{ij}(n)} + \mu * \Delta w_{ij}(n)$$

$$= \eta * e(n) * \acute{\sigma}[v(n)] * \Psi_{a,b}\big[\, v_{j\,(n)}\big] + \mu * \Delta w_{ij}(n) \qquad ....(7)$$

The translation coefficient in hidden layer can be adjusted according to [15]:

$$\Delta b_j\,(n+1) = -\,\eta * \frac{\partial E(n)}{\partial b_j(n)} + \mu * \;\Delta b_j\,(n)$$

$$= -\,\eta * e(n) * \acute{\sigma}[v(n)] * w_{ij}(n) * [\, v_{j\,(n)}] * \frac{1}{a_j\,(n)} + \mu.\Delta b_j\,(n) \qquad .... (8)$$

The dilation coefficient in hidden layer is updated as follow:

$$\Delta a_j\,(n+1) = -\,\eta * \frac{\partial E(n)}{\partial a_j(n)} + \mu * \;\Delta a_j\,(n)$$

$$= -\,\eta * e(n) * \;\acute{\sigma}[v(n)] * w_{ij}(n) * \;\Psi\,\grave{a}, b\,\big[\, v_{j\,(n)}\big] * \frac{v_j(n) - b_j\,(n)}{a_j(n)^2} + \mu * \Delta a_j\,(n) \qquad ..(9)$$

The wavelet functions which considered here called "morlet function":

$$\Psi(x) = \cos(1.75x) * exp^{-x^2} \qquad ..... (10)$$

As the general approximation theorem described in [16] applies, the usual sigmoid function used in this paper is as follows:

$$\sigma\,(x) = \frac{1}{1+exp^{-x}} \qquad ..... (11)$$

WNN Predictor

The work in WNNs has concentrated on forecasting future developments of DGPS corrections from values of x up to the current time. The proposed WNN in this paper is shown in Fig. (2), the choosing of the WNN parameters is also important. In this paper we used the WNN to predict the future values of GPS, the order was based on the experimental results in [15].

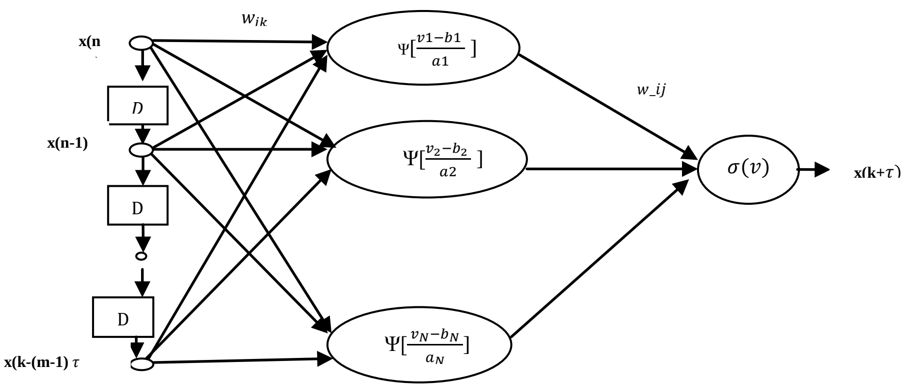


Figure (2): A proposed WNN for GPS prediction.

RBF Neural Networks

Radial Basis Function Neural Networks (RBFNNs) are characterized by a transfer function in the hidden unit layer having radial symmetry with respect to a center [17]. RBF neural network is a feed-forward three-layered network with single hidden layer. It consists of one input layer, one hidden layer and one output layer [18]. Each input neuron corresponds to an element of an input vector and is fully connected to the hidden layer neurons. Again, each of the hidden layer neurons also fully connected to the output neurons. The output of the net is given by the following expression [10]:

$$F(\overrightarrow{X}, \emptyset, w) = \sum_{i=1}^{m} \emptyset_i(\overrightarrow{x}) * w_i \qquad \ldots\ldots\ldots\ldots\ldots (12)$$

Where

$\emptyset = [\emptyset_i$: 1,….,m]are the basis functions set and w_i the associate weights for every Radial Basis Function (RBF). The basis function can be calculated as a Gaussian function using the following expression:

$$\emptyset(\vec{x}, \vec{c}, \vec{r}) = \exp\left[\frac{\|\vec{x}-\vec{c}\|}{r}\right] \qquad \ldots\ldots\ldots\ldots\ldots (13)$$

Where

c is the central point of the function $\emptyset$, *r* is its width, and *x* is the input vector.

The basic architecture of an RBFNN is a 3-layer network as shown in Fig. (3) [19].

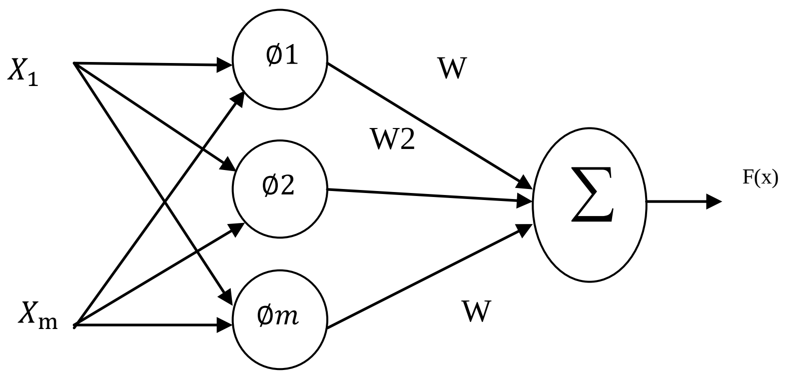


Figure (3): A proposed RBFNN for prediction of GPS.

Generally, the RBFNN training can be divided into two stages:

1. Determine the parameters of radial basis functions, i.e., Gaussian center and spread width.
2. Determine the output weight *w* by supervised learning method.

The first stage is very crucial, since the number and location of centers in the hidden layer will influence the performance of the RBFNN directly.

Simulation Results

In order to evaluate the accuracy of the prediction, the Root Mean Square (RMS) is computed as below:

$$\mathrm{RMS} = \sqrt{\sum_{i=1}^{M} \left(d(i) - y(i)\right)^2} \quad \text{.... (14)}$$

Where

M is the number of tested points, *d(i)* denote the estimated predicted path in (X, Y, Z), and *y(i)* present the real path of GPS in (X, Y, Z).

Fig. (6), shows the flow chart of WNN Algorithm, while Fig. (7), shows the flow chart of RBFNN Algorithm. the proposed algorithm and the parameter that is effected in the above methods is as follow :

1. No. of Input is (60 of X-axis & 60 of Y- axis & 60 of Z- axis).
2. No. of Output Neurons is (3 neurons).
3. No. of Hidden Layer is (15 Layers).
4. No. of Neurons in Hidden Layer is (56 Layers) &(η is 0.0001).

Different scenarios are taken for both algorithms; WNN and RBFNN to obtain the optimal predicted values for GPS prediction in the three directions (X, Y, Z), where:

Scenario *(I);* Table (1), illustrates the (Maximum, Minimum, RMS errors, Variance, and Standard Deviation) parameters, which represents the prediction error values in (X, Y, Z), (the difference between the estimated predicted path and real path of GPS that computed from the satellites reading values), for (1000 training iteration) using WNNs. Fig. (4a-c) shows the RMS errors in (X, Y, Z) for this scenario.

Scenario (II); Table (2), represents the prediction error values in (X, Y, Z), (like **Scenario (I)**), for (1000 training iteration) using RBFNN. Fig. (5 a-c) illustrates the RMS errors in (X, Y, Z) for this scenario.

So, the important parameters, (RMS errors), have very law values in the three directions (X, Y, Z) when using WNNs compared with RBFNN.

DISCUSSION

There are two points of view were used here to discuss the results:

Firstly; discuss the feature of the proposed work with the other related distinct researches. In reference [13], the performance of WNN is compared with Multilayer Perception (MLP) in the application of prediction; the experimental results demonstrate RMS errors are less than 0.4 meter after of WNNs prediction. In [18], introduced BP neural network and RBF Network's basic theory, compared these two characteristics of the network structure, while in the present work, demonstrate the comparison between the Wavelet and Radial Basis Function Neural Network characteristics of the network structure, with using MATLAB program.

The results show that the Wavelet Neural Networks method has a great approximation ability, suitability than Radial Basis Function Neural Networks, were highly effective predictions for accurate positioning and the RMS errors are 0.05 meter after using of Wavelet Neural Networks prediction.

Secondly, different scenarios are taken in this work, hence from tables (1 & 2) and Figs. (4 & 5), one can see that the RMS errors in (X, Y, Z) for GPS predictor will be much reduce when using Wavelet Neural Networks, rather than using Radial Basis Function Neural Networks, for the same satellites reading values taken from [20] and training iteration.

CONCLUSION

This paper presented a comparison between the Wavelet Neural Networks and Radial Basis Function Neural Networks for GPS prediction, from the results, one can concludes that:

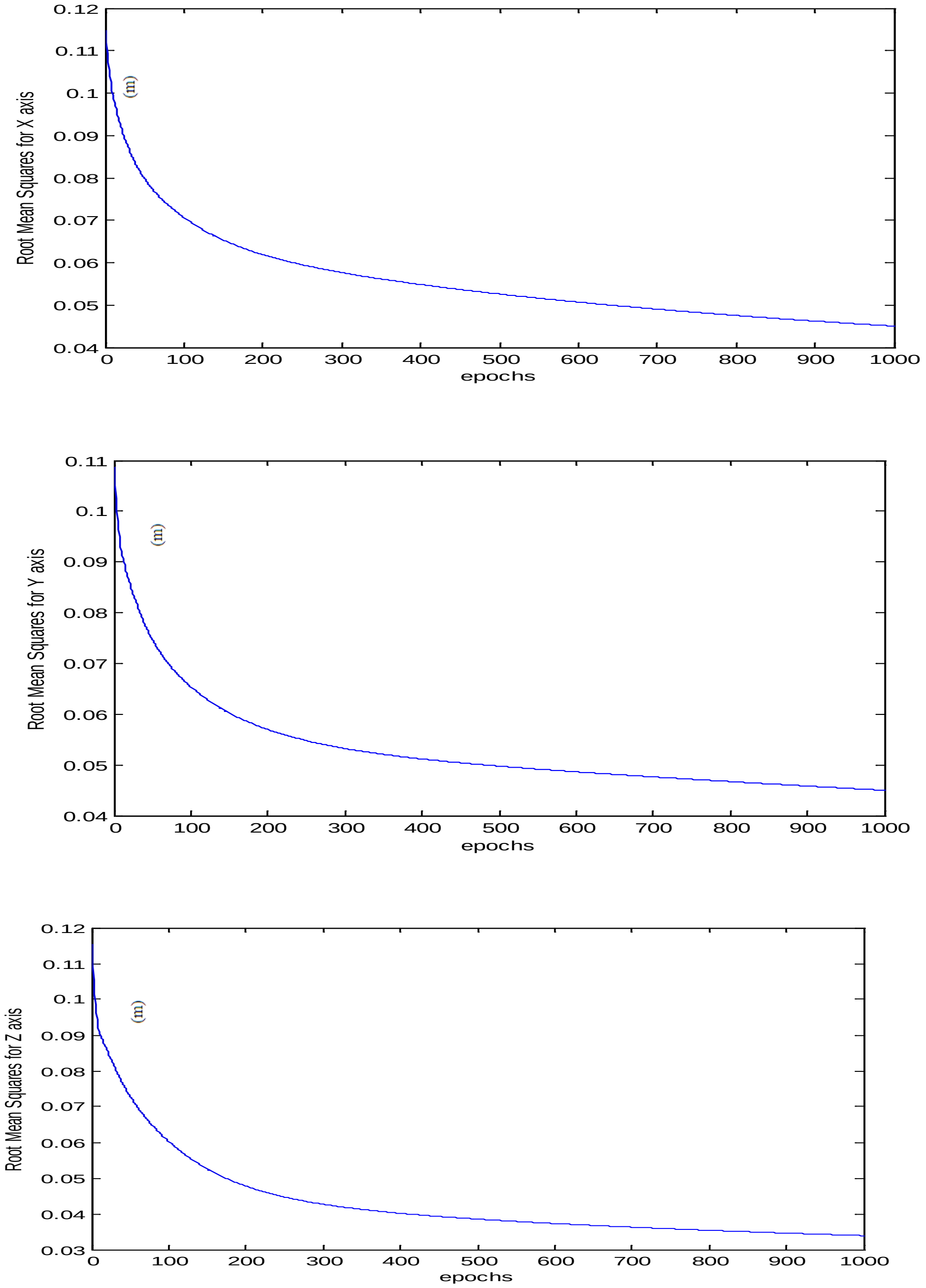
1. The prediction errors statistical significance characteristics including (Maximum, Minimum, RMS errors, Variance, and Standard Deviation), between estimated predicted path, and the real path of GPS (which are computed from the satellites reading values) in different scenarios (using MATLAB programming for 1000 training iteration), the results present highly effective predictions for accurate positioning of GPS reading.
2. Predictions of RMS errors are less than 0.05 meter after used WNNs for prediction; it has great ability, suitability and more stability for the GPS prediction than RBFNN.

Table (1): Prediction Errors Statistical Significance Characteristics Using WNNs (morlet).

Parameters	X (m) Component	Y (m) Component	Z (m) Component
Max.	0.1201	0.1223	0.1605
Min.	0.0444	0.0439	0.0326
RMS	0.0590	0.0543	0.0461
Variance	1.3930e-04	9.7597-05	2.0480e-04
Standard Deviation	0.0118	0.0099	0.0143

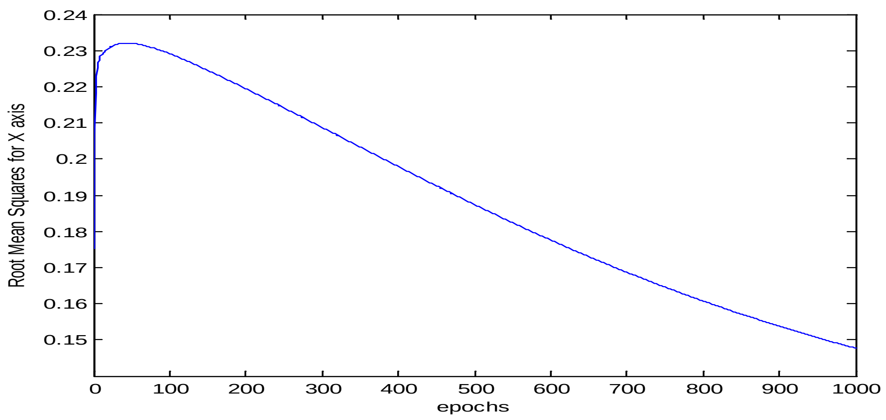
Table (2): Prediction Errors Statistical Significance Characteristics Using RBFNNs.

Parameters	X (m) Component	Y (m) Component	Z (m) Component
Max.	0.2321	0.0610	0.2960
Min.	0.0254	0.0059	0.0294
RMS	0.1149	0.0308	0.1431
Variance	0.0039	2.381e-04	0.0061
Standard Deviation	0.0627	0.0168	0.0782

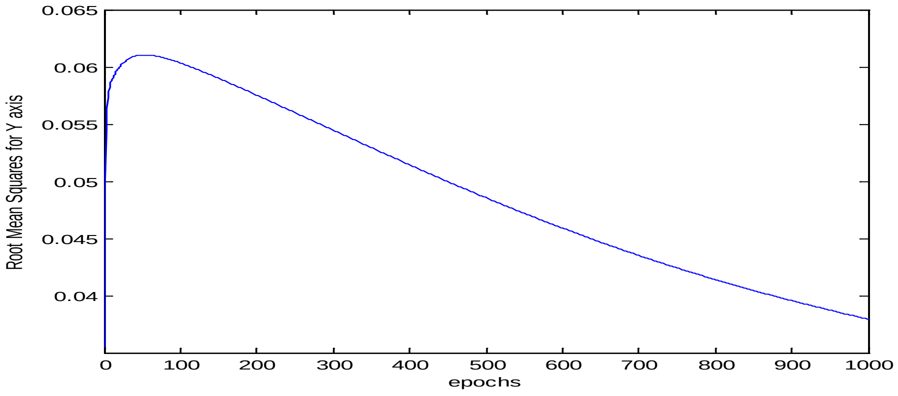


-a- **-b-** **-c-**

Figure (4): Root Mean square error using WNN for GPS prediction.
a-In x-axis. b- In y-axis. c- In z-axis.



-a-



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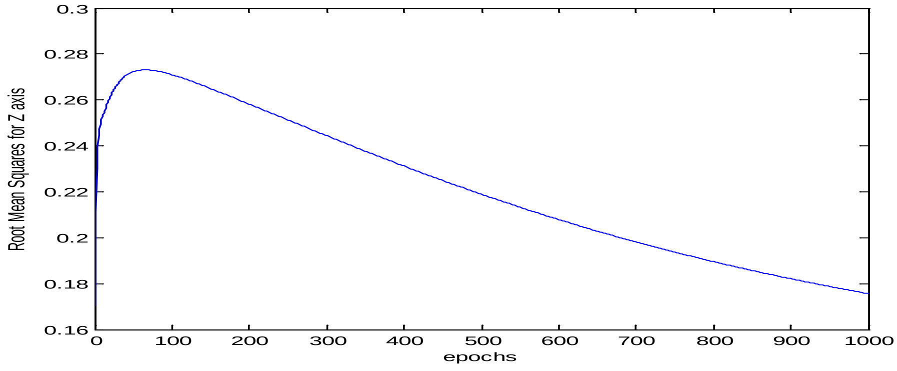

-c-

Figure(5): Root Mean square error using RBFNN for GPS prediction.
a-In x-axis. b- In y-axis. c- In z-axis.

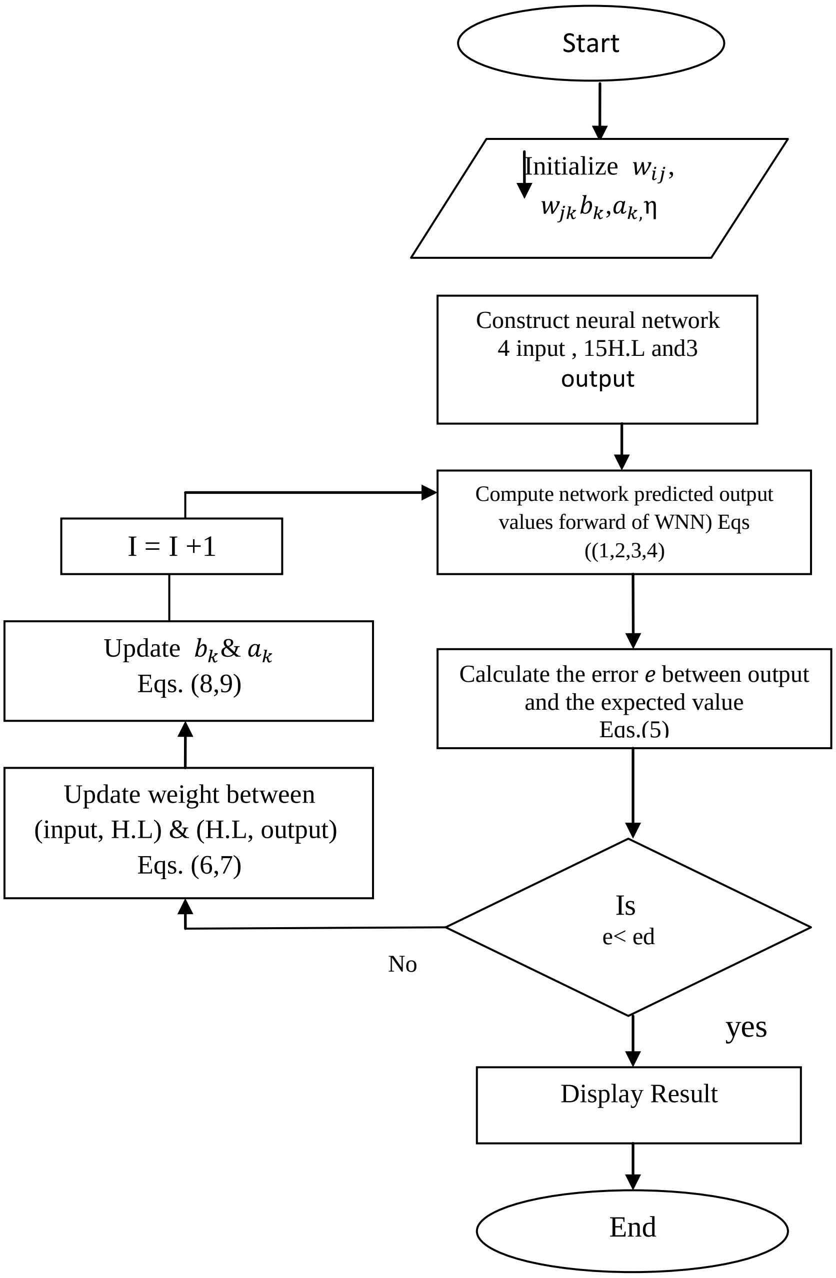

Figure (6): Flow chart of WNN Algorithm.

- ed : means minimum error = 0.05
- I : means number of iteration=1000

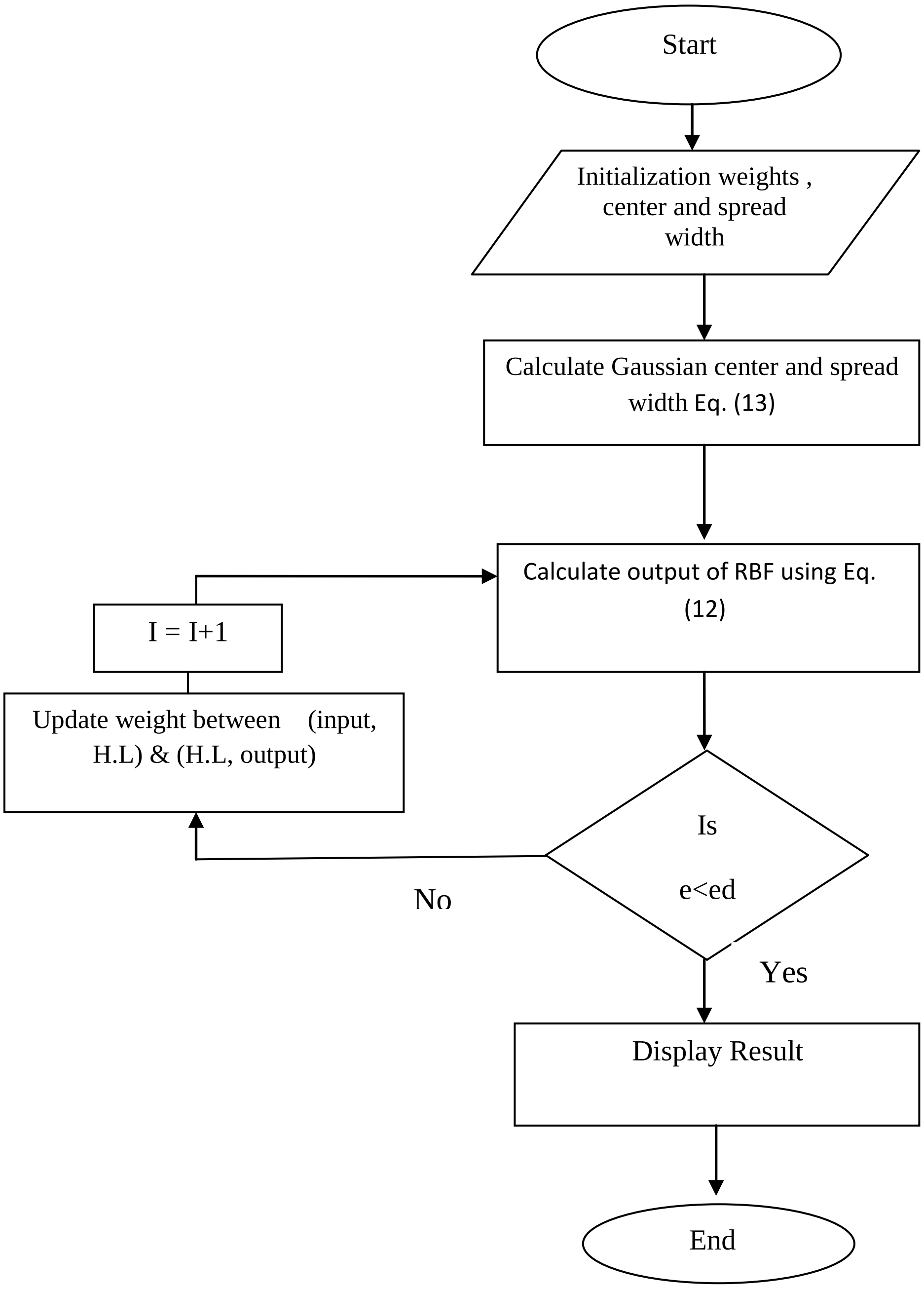

Figure (7) Flow chart of RBFNN Algorithm.

- ed : means minimum error = 0.05
- I : means number of iteration=1000

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